A PROJECT ON

Brain Tumor Detection using Convolutional Neural Networks

Submitted in partial fulfilment of the requirement for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE & ENGINEERING with specialization in DS & AI

Submitted by:

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the Project Report entitled **"Brain Tumor Detection Using Convolutional Neural Networks"** in partial fulfilment of the requirements for the award of the Degree of Bachelor of Technology in Computer Science and Engineering and submitted in the Department of Computer Science and Engineering of the Graphic Era (Deemed to be University), Dehradun is an authentic record of my own work carried out during a period from **August-2022 to May-2023** under the supervision of **Dr. Vijay Singh (Professor) and Dr. Ashwini Kumar Singh (Associate Professor)** Department of Computer Science and Engineering, Graphic Era (Deemed to be University).

The matter presented in this dissertation has not been submitted by me/us for the award of any other degree of this or any other Institute/University.

Arif Ansari 2015153

signature

signature

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

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Supervisor **Head of the Department**

External Viva

Name of the Examiners: **Signature with Date**

1.
2.

Abstract

Identifying brain tumors in their early stages is crucial as they can exert pressure on neighbouring tissues, resulting in symptoms like headaches, nausea, and balance problems. Magnetic resonance imaging (MRI) has emerged as a superior technique for detecting brain tumors compared to computed tomography due to its higher level of detail and consistency. To identify brain tumors or neoplasms, researchers have explored various methodologies, and this paper aims to review relevant research publications to identify the most effective algorithms. These algorithms typically involve steps such as brain image pre-processing, segmentation, feature extraction, grouping, and tumor detection.

Keywords— Image Processing, Tumor Detection, Convolutional Neural Networks (CNN), Magnetic Resonance Image(MRI), Computer Aided Detection System, Feature Extraction, Classification.

Acknowledgement

Any achievement, be in scholastic or otherwise does not depend solely on the individual effort but on the guidance, encouragement and co-operation of intellectuals, elders, and friends. A few personalities in their own capacity have helped me in carrying out this project work.

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Chapter 1

Introduction

In the following sections, a brief introduction and the problem statement for the work has been included.

1.1 Project Introduction

A brain Tumor is an abnormal cell growth or mass in the brain. There are many different types of brain tumours, such as medulloblastoma, chondrosarcoma, and chordoma. Some brain tumours are benign (noncancerous), while others are cancerous (malignant). Brain cancers can start in the brain (primary brain tumours) The rate at which a brain tumour grows varies substantially. The rate of growth of a brain tumour, as well as its location, define how it will influence the function of your neurological system. The type of brain tumour you have, as well as its size and location, influence your treatment options. Exposure to substantial levels of radiation from X-rays or previous cancer treatment is the only known environmental cause of brain tumours.

A brain tumour starts in the brain cells and spread to the rest of the body (as depicted). As the tumour grows, it exerts pressure on adjacent brain tissue and alters its function, resulting in indications and symptoms such as headaches, nausea, and balance issues.

MRI with tumour is difficult to segment due to a combination of the following factors:

1. The tumour mass effect causes non-tumor structures to distort.

2. Edema and tumour infiltration of brain tissue (swelling). Edema appears primarily in white matter regions around the tumour.

3. The change from tumour to edema is slow, and the line between the two forms is sometimes difficult to distinguish.

T1w with contrast enhancement (usually using gadolinium) is the conventional MRI modality for detecting tumours, although is not always the best option. Blood arteries and cortical fluid often highlighted alongside tumours, but necrotic tissue sections of the tumour not increased at all. By merely thresholding the contrast enhanced t1w image, it is nearly hard to segregate turns

1.2 Problem Statement

The modern equipment and the computer vision is helping the people in many ways, their usage in the medical field. As the tumour grows, it exerts pressure on adjacent brain tissue and alters its function, resulting in indications and symptoms such as headaches, nausea, and balance issues. Early detection of a brain tumour provides the possibility for effective medical therapy. When compared to computed tomography pictures, magnetic resonance imaging (MRI) images have been found to be more detailed and consistent. There are several methods for detecting brain tumours or neoplasms. After reviewing various relevant research publications, this Project Report discusses the most competent and effective algorithms. Brain image pre-processing, segmentation, feature extraction, grouping, and detection of the tumour are the methodologies in most research.

The details of the proposed CNN model are mentioned in the proposed methodology part of this paper.

1.3 Objectives

Brain tumor occurs because of anomalous development of cells. It is one of the major reasons of death in adults around the globe. Millions of deaths can be prevented through early detection of brain tumor. Earlier brain tumor detection using Magnetic Resonance Imaging (MRI) may increase patient's survival rate. In MRI, tumor is shown more clearly that helps in the process of further treatment. This work aims to detect tumor at an early phase.

The objectives of Process of detection of Brain Tumor using MR image analysis are broadly divided.

- Study of pre-processing of MR images.
    - Image acquisition
    - Adaptive filtering
- Study of Image Analysis of MR images
    - Segmentation
    - Feature Extraction
    - Enhancement
    - Development of neural network algorithm for Classification and Detection of Brain Tumor.

Chapter 2

Literature Survey/ Background

2.1 A Survey on Brain Tumor Detection Using Image Processing Techniques: Biomedical Image Processing is a rapidly growing field that involves various types of imaging techniques to identify abnormalities in the human body. The primary goal of medical imaging is to extract accurate information from images with minimal error. MRI is considered the most reliable and safe method as it does not involve harmful radiation. Tumor segmentation using MRI involves four main categories: pre-processing, segmentation, optimization, and feature extraction. A survey has been conducted by compiling the research of professionals in the field.

2.2 Application of Edge Detection for Brain Tumor Detection: Brain tumors can be fatal if they grow beyond 50%, making fast and accurate detection essential. This paper proposes a machine learning model for detection of the edges of a brain tumor. The process begins with acquiring an MRI scan, where MRI technique is applied to determine the size and location of the brain tumor. Noise filters being used to remove the noise, and other enhancement techniques are applied to the MRI scan. Morphological operations are then applied to extract the region affected by the tumor, followed by verification using watershed segmentation.

2.3 Brain Tumor Analysis Using Deep Learning and VGG-16 Ensembling Learning Approaches: The promise of deep learning, in particular convolutional neural networks (CNNs) and the Visual Geometry Group (VGG 16), for MRI-based brain tumour detection is discussed in this article. The authors created a method that creates convolutional feature maps using a CNN model framework and classifies them to produce recommendations for tumour regions. The method outperformed traditional algorithms for finding brain tumours in a dataset of 253 MRI brain pictures, 155 of which showed tumours. The VGG 16 and Ensemble Model obtained 98.5% and 98.14% accuracy, compared to 96% accuracy for the CNN. The report makes recommendations for future studies in this area.

2.4 Brain Tumor Detection and Classification Using Deep Learning and Sine-Cosine Fitness Grey Wolf Optimization: The main topic of the paper is the application of deep learning methods for brain tumour classification and diagnosis. A Brain Tumour Classification Model based on Convolutional Neural Networks (BCM-CNN) is introduced using the suggested method. To improve the precision of brain tumour diagnosis, our model makes use of a pre-trained neural network architecture, specifically Inception-ResNetV2. A binary classification representing a normal instance as 0 and the presence of a tumour as 1 is the model's output. The paper introduces the Adaptive Dynamic Sine-Cosine Fitness Grey Wolf Optimizer (ADSCFGWO) algorithm to modify the hyperparameters and improve the performance of the model. The experimental findings show that, when tested on the BRaTS 2021 Task 1 dataset, the BCM-CNN achieves an outstanding accuracy of 99.98%. According to the paper's findings, deep learning techniques may help in the creation of automated systems that can recognise or categorise brain tumours with great accuracy in a short amount of time.

2.5 Brain tumor detection and classification using machine learning - A comprehensive survey: Detecting brain tumors accurately using magnetic resonance imaging remains a formidable challenge despite considerable research efforts and promising results. The difficulty arises from the diverse characteristics of tumors in terms of their location, shape, and size. The main goal of this survey is to present a comprehensive literature review on brain tumor detection, covering various aspects such as anatomical considerations, publicly available datasets for research purposes, enhancement techniques to improve image quality, segmentation methods to separate tumor regions from the surrounding tissues, feature extraction techniques to capture relevant tumor characteristics, classification algorithms to distinguish between tumor and non-tumor regions, and the application of deep learning, transfer learning, and quantum machine learning in this domain. The survey concludes with a discussion on the advantages and limitations of existing approaches, recent developments, and future trends in brain tumor detection. By examining the current state of the field, this survey aims to provide valuable insights for researchers and contribute to further advancements in brain tumor detection techniques.

2.6 Brain Tumor Detection based on Machine Learning Algorithms: Automated detection of tumors in Magnetic Resonance Imaging (MRI) has become important for medical diagnostic applications. Conventional methods for defect detection in MRI brain images involve human inspection, which is impractical for large amounts of data. This paper proposes a machine learning-based approach for automated brain tumor detection in MRI images, which involves preprocessing, texture feature extraction using GLCM, and classification using machine learning algorithms. This approach can save radiologist time and overcome the complexity and variance of brain tumors.

2.7 Brain tumor detection based on Naïve Bayes Classification: This study primarily addresses the detection of cancer-affected brain tissues, with a specific focus on Glioblastoma multiforme (GBM), which is a highly aggressive brain tumor. The proposed method utilizes Naïve Bayes classification to accurately identify tumor regions. The research incorporates various techniques, including the utilization of a brain MRI database, preprocessing steps, morphological operations, pixel subtraction, maximum entropy thresholding, extraction of statistical features, and the implementation of a Naïve Bayes classifier-based prediction algorithm. The method demonstrates the ability to effectively detect tumors in different brain regions, including the middle region, and achieves an impressive overall accuracy rate of 94% when evaluated on a dataset comprising 50 MRI images.

2.8 Brain Tumor Detection by using Artificial Neural Network: This study investigates the use of artificial neural networks (ANN) in place of time- and error-prone human evaluation in the detection of brain tumours using magnetic resonance imaging (MRI). The study describes the various processes involved in the computer-aided detection system (CAD), including MRI image pre- and post-processing, segmentation using thresholding, feature extraction using statistical feature analysis, and classification using a feed-forward backpropagation neural network with supervised learning. The ANN-based technique identified brain tumours with 99% accuracy and 97.9% sensitivity.

2.9 Brain Tumor Detection Using Convolutional Neural Network: The Fuzzy C-Means clustering technique, conventional classifiers, and a convolutional neural network (CNN) are combined in the research to give a suggested method for extracting brain tumours from 2D Magnetic Resonance brain pictures. The study makes use of a real-time dataset that includes various tumour types, sizes, locations, forms, and image intensities. Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Multilayer Perceptron (MLP), Logistic Regression, Naive Bayes, and Random Forest are six examples of conventional classifiers used. In addition, Keras and Tensorflow are used to create a Convolutional Neural Network (CNN). The main goal is to distinguish between normal and aberrant pixels using statistical and texture-based criteria. The CNN shows strong performance and the potential for efficient brain tumour identification with a remarkable accuracy rate of 97.87%.

2.10 Brain Tumor Detection Using Deep Neural Network and Machine Learning Algorithm: Research on the detection of brain tumours in Magnetic Resonance Imaging (MRI) pictures using Deep Neural Networks (DNNs), particularly Convolutional Neural Networks (CNNs), shows tremendous potential. For picture categorization, the Softmax Fully Connected layer achieves a remarkable accuracy of 98.67%. Additionally, the CNN achieves an accuracy of 97.34% when paired with the Radial Basis Function (RBF) classifier and 94.24% when combined with the Decision Tree (DT) classifier. A sensitivity, specificity, and precision evaluation of the network's performance is also included in the study. The CNN's Softmax classifier, which achieved an astonishing 99.12% accuracy on the test data, stands out as having the highest accuracy.

This novel method introduces a combination of feature extraction techniques with the CNN model for tumor detection within brain images, resulting in improved accuracy when compared to traditional methods. Early and accurate detection of brain tumors utilizing DNNs can greatly assist physicians in diagnosing and treating patients more effectively, ultimately leading to enhanced quality of life and increased life expectancy for affected individuals.

2.11 Brain Tumor Diagnosis Using Machine Learning, Convolutional Neural Networks, Capsule Neural Networks and Vision Transformers, Applied to MRI: A Survey: This paper provides a detailed exploration of various techniques utilized in the classification and segmentation of brain tumors, with a specific focus on machine learning (ML) approaches such as Convolutional Neural Networks (CNNs), Capsule Neural Networks (CapsNets), and Vision Transformers (ViTs). The primary objective is to highlight the significance of non-invasive tumor grade assessment in determining optimal treatment plans.

Although CNNs have shown promise in the identification of brain tumours, they might not be resistant to changes in input. Working with medical imaging datasets is made more advantageous by CapsNets' resistance to rotations and affine translations. The issue of long-range reliance in CNNs has also been addressed, and a solution called Vision Transformers (ViTs) has been suggested.

The study gives a thorough analysis of various methods, emphasising their performance traits, drawbacks, and potential future research areas. The goal is to provide a useful tool for future research and development in the area of brain tumour classification and segmentation.

2.12 CNN Based Multiclass Brain Tumor Detection Using Medical Imaging: Using CNNs for brain tumor classification is indeed a popular and effective approach in medical image analysis. The ability to accurately classify brain tumors into different grades can significantly impact treatment plans and patient outcomes. It's good to see that the proposed model was able to classify MRI images into four different classes with such a high level of accuracy. However, it's worth noting that the evaluation of a medical imaging model goes beyond just accuracy. Sensitivity, specificity, and other performance metrics should also be considered, and the model should be validated on a large and diverse dataset to ensure its generalizability.

2.13 Computer Aided System for Brain Tumor Detection and Segmentation: It is encouraging to learn that the suggested method detects and segments brain tumours in MR images with accuracy. To give greater insight into the effectiveness of the suggested strategy, it would be useful to offer some quantitative findings, such as sensitivity, specificity, and accuracy. To show the proposed method's superiority or impact on the field, it would also be helpful to compare how well it performs against approaches already in use.

2.14 Deep Convolutional Neural Networks Model-based Brain Tumor Detection in Brain MRI Images: The model's superior performance to currently used traditional approaches and high total accuracy of 96% show the potential of AI in healthcare. With the aid of DCNNs, brain tumour diagnoses can be made much more quickly and with less technical knowledge, leading to earlier identification and quicker treatment. The suggested model's precision, sensitivity, and F1-score indicate that it has good reliability and can be a useful tool for clinical professionals in making precise diagnoses. The performance of the model is further supported by the average precision-recall score, Cohen's Kappa, and AUC. Overall, this work represents a positive development towards a self-contained system for diagnosing brain tumours that could greatly enhance patient outcomes.

2.15 Deep Learning Based Brain Tumor Detection and Classification: In this paper, two deep learning-based approaches, YOLO and FastAi, are proposed for the detection and classification of brain tumors. The aim of these approaches is to automate the detection process, enabling early diagnosis and reducing the likelihood of errors. The reported accuracies of 85.95% and 95.78% demonstrate the potential of these approaches for real-time brain tumor detection.

The utilization of YOLO, a state-of-the-art framework of object detection, and FastAi, a deep learning library, enhances the accuracy and speed of the detection process. By leveraging these cutting-edge technologies, the proposed approaches offer improved efficiency and effectiveness in identifying brain tumors.

The significance of early detection in brain cancer cannot be overstated, as it enables prompt treatment interventions that can greatly improve patient outcomes. The implementation of these deep learning-based approaches holds promise in facilitating early detection and, subsequently, early treatment, leading to more favorable outcomes for individuals affected by brain tumors.

2.16 Design and implementing Brain Tumor Detection using Machine Learning approach: Brain tumour detection and segmentation are essential for early diagnosis and successful treatment. Brain tumour regions can often be located via Magnetic

Resonance Imaging (MRI) segmentation. Convolutional Neural Networks (CNNs) are used in this study's efficient automatic segmentation method to provide precise segmentation and classification.

Data collection, pre-processing, average filtering, segmentation, feature extraction, and the use of CNNs for classification and identification are just a few of the processes in the suggested method. Notably, the CNN architecture's usage of tiny 3 × 3 kernels improves the segmentation process' effectiveness.

In the field of medicine, the combination of machine learning and data mining methods has shown to be quite successful, particularly in the early diagnosis and prevention of brain tumours. Researchers can increase the precision and speed of tumour segmentation by utilising these cutting-edge technologies, facilitating early diagnosis and intervention.

Overall, the suggested technique presents a viable strategy for automating CNN-based brain tumour segmentation, which could enhance patient outcomes and improve diagnostic accuracy.

2.17 Image Processing Techniques for Brain Tumor Detection: A Review: In order to analyse, diagnose, and plan treatment for brain tumours, medical personnel use MRI imaging, which enables them to monitor the disease's development. However, because of the complex anatomy of the brain, detecting brain tumours with MRI scans poses major difficulties. MRI scans provide better results than other imaging modalities including CT, Ultrasound, and X-ray. A variety of pretreatment and post processing approaches can be used to help in brain tumour detection. These methods include edge detection, histogram analysis, thresholding, filtering, contrast enhancement, edge detection, picture segmentation, and morphological procedures. The MATLAB image processing tool offers a perfect framework for putting these strategies into practice and successfully identifying brain tumour images.

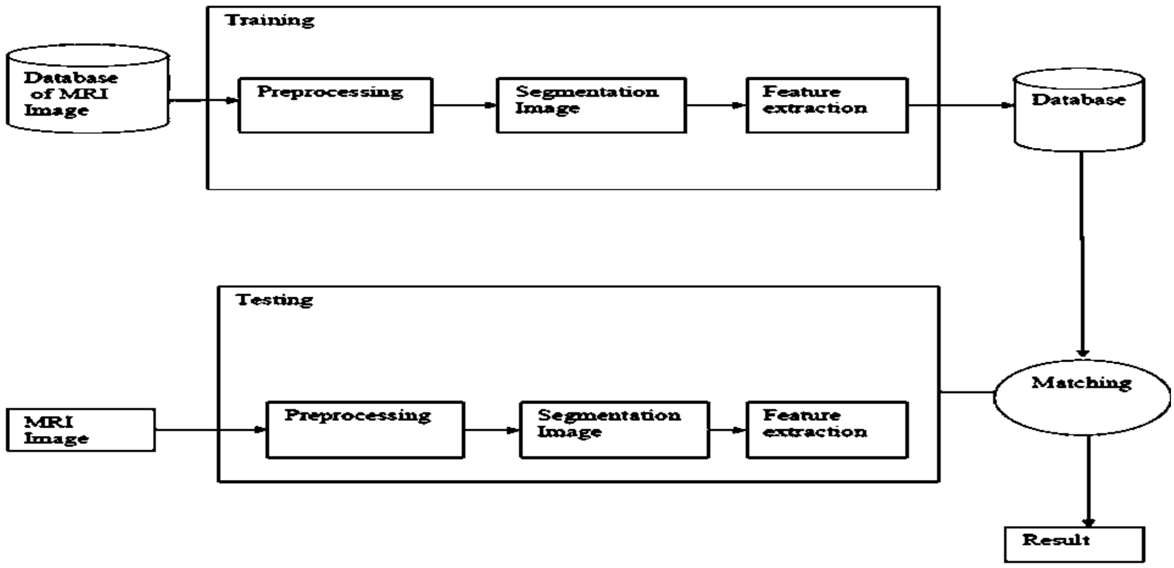
2.18 Brain Tumor Detection Using Neural Network: The variety of patterns and intensities displayed by brain tumours make it difficult to detect them in magnetic resonance imaging (MRI). The authors of this study examine various computer-aided detection systems for brain tumours using MRI, concentrating on different stages of the system. They use updated image segmentation techniques to extract tumour locations from MRI data in order to do this. In addition, the authors suggest a modified probabilistic neural network (PNN) model for automated brain tumour classification that combines learning vector quantization (LVQ) with picture and data analysis. The findings of simulations and experiments show that the suggested system is superior to traditional PNN techniques, with a remarkable accuracy of 100% in brain tumour classification.

Chapter 3

Requirements and Methodologies

The first portion of this research is concerned with the detection of a brain tumour, which is defined as the existence of the tumour in the given MRI. The classification of the tumour is found in the other component, which is the second part. Here, we'll examine the MRI scans to determine whether the tumour is benign or malignant. The schematic represents our method in general. The input photos will go through several steps, which can be summarized as follows.

3.1 Experimental Methodology



System Architecture

Figure 3.1

3.1.1 MODULE 1: - Image Acquisition

The MRI pictures are first captured, and then these images are fed into the pre-processing stage. Collecting MRI pictures is the basic mechanism by which the process begins.

3.1.2 MODULE 2: - Pre-processing

1.) Pre-processing is necessary because it improves the image data and improves some of the image attributes that are relevant for subsequent processing.

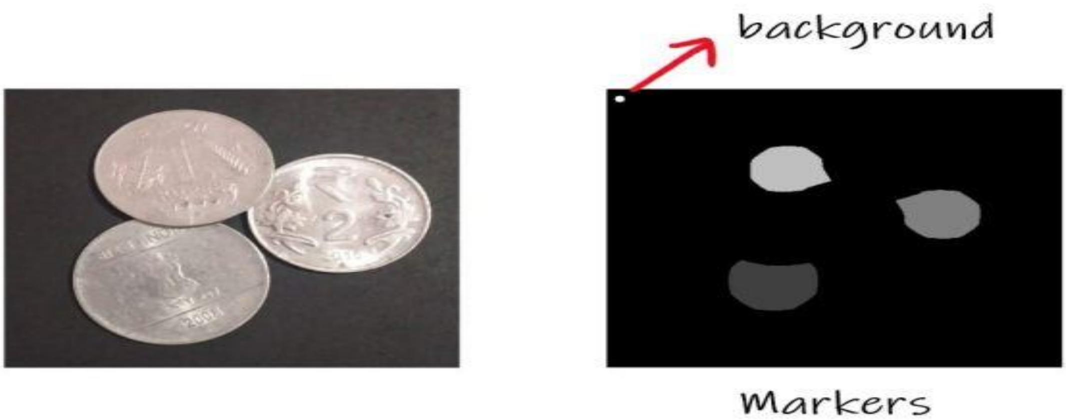
2.) The RGB MRI picture is transformed to grayscale, and the median filter is used to remove noise from brain MR images. Because great accuracy is required, the noise must be eliminated before further processing.

3.) Canny edge detection is used to detect edges in a filtered image. For image segmentation, the detected image of the edges is necessary.

4.) Watershed segmentation is used to pinpoint the tumour's position in the brain picture.

3.1.3 MODULE 3: - Segmentation

1) Segmentation is the process of dividing an image into multiple segments.
2)The goal of segmentation is to transform an image's representation into something that is easier to examine.
3) The process of separating the tumour from normal brain tissues is known as segmentation.
4) The watershed segmentation technique is used to locate the tumour in MRI images.
5) The label picture is the outcome of watershed segmentation. The different things that are identified in the label image will have distinct pixel values.

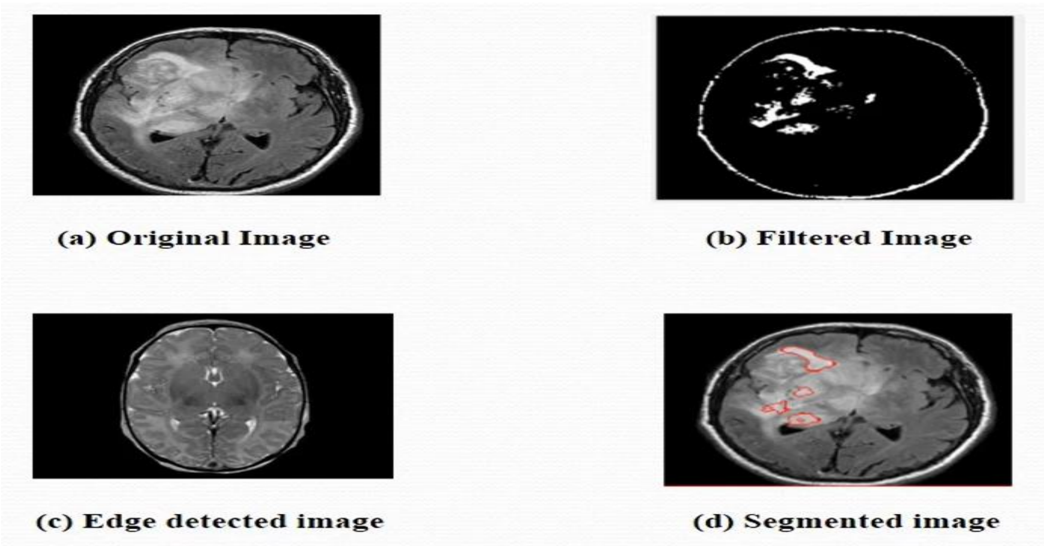


Watershed Segmentation [iPython.com]

Figure 3.2

3.1.4 MODULE 4: - Feature Extraction

1) When an algorithm's input is too vast and redundant to process, it's turned into a smaller set of features called a feature vector. Feature extraction is the process of transforming this input data into a set of features. The main features necessary for picture categorization are extracted in this step.
2) A segmented brain MRI picture is employed, and texture features from the segmented image are retrieved, revealing the image's texture property.
3) Conv2d is used to extract these characteristics since it is a reliable and high-performing approach.
4) Conv2d layers are commonly employed in image recognition jobs to achieve high accuracy. They do, however, necessitate a lot of calculations and use a lot of RAMS. The complexity of the convolution procedure is reduced by using dilated or aurous convolutions.



Segmentation of Brain MRI Image

Figure 3.3

3.1.5 MODULE 5: - Classification

1. MRI brain picture classification into normal or pathological.
2. Each node in a multilayer perceptron is a neuron that has a nonlinear activation function.
3. We can determine whether a tumor is present or not using the above components.
4. This procedure aids in determining the tumor's size, shape, and location.

3.2 Experimental Results

The experiment was carried out on 3000 brain MR images. From each image, the texture-based features are extracted and classification is used. The texture-based features such as energy, contrast, correlation, and homogeneity are extracted using deep learning methods. For the model building keras sequential model is used along with some layers like conv2d, maxpooling2d, activation, flatten, dense. for the normalization, 'he_uniform' kernel initializer is used and to reduce the overfitting dropout are also used.

3.2.1 Model Performance Evaluation

This segment covers the performance evaluation of employed and train CNN model. The model proposed in this paper was implemented on the Brain MRI dataset which consists of 3000 brain MR images where 1500 images show indications of tumours and 1500 are not. As the model is trained, precision, sensitivity or recall, F1-score, and average precision-recall score measurement to clarify the supremacy of the proposed approach is interpreted, instead of merely focusing on the classification accuracy as a model performance evaluating metric. If a double class classification issue is considered, the performance of a classifier model can be laid out as a confusion matrix shown in Table 1.

Table 3.1 Confusion Matrix

	Expected Positive	Expected Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

The parameters TP symbolize the true positive for the number of positive brain tumor images properly classified, TN depicts the number of images that were classified correctly. Conversely, FP denotes false-positive images which the number of positive images incorrectly classified as negative, and FN denotes the false-negative as represents the number of negative images misclassified as positive.

With reference to the confusion matrix provided in Table 1, the overall accuracy can be determined with the help of Equation (i).

$$\text{Accuracy}(\%) = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \quad \text{(i)}$$

However, as mentioned earlier, the precision, sensitivity, or recall and the F1-score values for analysing the CNN model's performance is also evaluated. The equations of these metrics are provided in Equation (ii), (iii) and (iv) respectively. The precision value represents the classifier model's exactness. On the other hand, the recall value represents the model's completeness.

$$\text{Precision(PPV)} = \frac{\text{TP}}{\text{TP+FP}} \quad \text{(ii)}$$

$$\text{SENSITIVITY} = \frac{\text{TP}}{\text{TP+FN}} \quad \text{(iii)}$$

$$\text{F1} - \text{score} = 2 \text{ x} \frac{\text{Precision} * \text{recall}}{(\text{precision} + \text{recall})} \quad \text{(iv)}$$

Here is the snapshot of my model's performance evaluating metrics with their performance score respectively:

```
Confusion Matrix:
 [[340   3]
 [  9 248]]
              precision    recall  f1-score   support

           0       0.97      0.99      0.98       343
           1       0.99      0.96      0.98       257

    accuracy                           0.98       600
   macro avg       0.98      0.98      0.98       600
weighted avg       0.98      0.98      0.98       600
```

Confusion Matrix

Fig 3.4

Table 3.2

Performance of proposed CNN Model

Performance Evaluating Metrics	Performance Score
Precision	0.98
Sensitivity or Recall	0.98
F1-Score	0.98
Average Precision -Recall Score	0.98
Accuracy	0.98

Chapter 4

Coding / Coding Template

TRAIN CODE:

```
import numpy as np
from PIL import Image
import os
import cv2
image_directory='datasets/'

no_tumor_images=os.listdir(image_directory+ 'no/')
yes_tumor_images=os.listdir(image_directory+ 'yes/')
dataset=[]
label=[]

# print(no_tumor_images)

# path='no0.jpg'

# print(path.split('.')[1])

for i , image_name in enumerate(no_tumor_images):
    if(image_name.split('.')[1]=='jpg'):
        image=cv2.imread(image_directory+'no/'+image_name)
        image=Image.fromarray(image,'RGB')
        image=image.resize((64,64))
        dataset.append(np.array(image))
        label.append(0)

for i , image_name in enumerate(yes_tumor_images):
    if(image_name.split('.')[1]=='jpg'):
        image=cv2.imread(image_directory+'yes/'+image_name)
        image=Image.fromarray(image, 'RGB')
        image=image.resize((64,64))
        dataset.append(np.array(image))
        label.append(1)

dataset=np.array(dataset)
label=np.array(label)

from sklearn.model_selection import train_test_split
#x = input features
#y = output feature
x_train, x_test, y_train, y_test=train_test_split(dataset, label, test_size=0.2,
random_state=0)

# Reshape = (n, image_width, image_height, n_channel)
```

```
# print(x_train.shape)
# print(y_train.shape)

# print(x_test.shape)
# print(y_test.shape)

#installing the normalization library from keras then assigning the training and testing data
from keras.utils import normalize
x_train=normalize(x_train, axis=1)
x_test=normalize(x_test, axis=1)

# categorising the training and testing data
from keras.utils import to_categorical
y_train=to_categorical(y_train , num_classes=2)
y_test=to_categorical(y_test , num_classes=2)

# Building the model
# 64,64,3
# Required Libraries
import tensorflow as tf
from tensorflow import keras
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D
from keras.layers import Activation, Dropout, Flatten, Dense

model=Sequential()

model.add(Conv2D(32, (3,3), input_shape=(64,64, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Conv2D(32, (3,3), kernel_initializer='he_uniform'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Conv2D(64, (3,3), kernel_initializer='he_uniform'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Flatten())

model.add(Dense(64))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(2))
model.add(Activation('softmax'))

model.compile(loss='categorical_crossentropy',optimizer='rmsprop',
metrics=['accuracy'])
```

```
model.fit(x_train, y_train,
batch_size=16,
verbose=1, epochs=10,
validation_data=(x_test, y_test),
shuffle=False)

from sklearn.metrics import confusion_matrix

# Predict the labels for the test set
y_pred = model.predict(x_test)
y_pred = np.argmax(y_pred, axis=1) # convert to class labels

# Calculate the confusion matrix
cm = confusion_matrix(np.argmax(y_test, axis=1), y_pred)

# Print the confusion matrix
print("Confusion Matrix:\n", cm)

from sklearn.metrics import classification_report
# Print the classification report
print(classification_report(np.argmax(y_test, axis=1), y_pred))

model.save('BrainTumor10EpochsCategorical.h5')
```

Chapter 5

Testing

TEST CODE:

```
import cv2
from keras.models import load_model
from PIL import Image
import numpy as np

model=load_model('BrainTumor10EpochsCategorical.h5')

image=cv2.imread('C:\\Users\PC1\OneDrive\Desktop\major project\pred\pred34.jpg')

img=Image.fromarray(image)

img=img.resize((64,64))

img=np.array(img)

input_img=np.expand_dims(img, axis=0)

result = model.predict(input_img)
#result_final=np.argmax(result,axis=1)
print(result)
```

Chapter 6

Result and Discussion

Here is the snapshot of my model's performance evaluating metrics with their performance score respectively:

```
Confusion Matrix:
 [[340   3]
 [  9 248]]
              precision    recall  f1-score   support

           0       0.97      0.99      0.98       343
           1       0.99      0.96      0.98       257

    accuracy                           0.98       600
   macro avg       0.98      0.98      0.98       600
weighted avg       0.98      0.98      0.98       600
```

Final Result

Fig 6.1

Table 6.1

Table of Performance

Performance Evaluating Metrics	Performance Score
Precision	0.98
Sensitivity or Recall	0.98
F1-Score	0.98
Average Precision -Recall Score	0.98
Accuracy	0.98

Chapter 7

Comparative Analysis

Ref.	Year	Methodology/ Approach	Dataset	Result	Drawback
1	2020	CNN	Fig-share Total Images (3064) from 233 patients	87% and 92%	No training time has been mentioned
2	2019	PNN and Classification CNN	KaggleTCIA	90% Accuracy	Lack of comparative analysis
3	2019	R-CNN and SVM	Pvt Dataset	95% Accuracy	Rapid conversion convolutional feature map into the region proposed
4	2020	Inception Pre-trained CNN	BRATS 13,14,17,18	92% Classification	Complex Approach
5	2020	ELM-LRF CNN	Figshare dataset (3064 images)	97%	Small Training Data
6	2019	CNN	Kaggle	Accuracy 92.3%	Basic Model
7	2020	R.N.N.	Private dataset comprising 1000 images	Classification 96% Specificity 98% Sensitivity 97%	There was no specific place. This process is examined.
Proposed Model	**2023**	**C.N.N.**	**M.R.I. Dataset (Kaggle)**	**Accuracy 97.67%-99% Precision 98% Sensitivity 98% F1-Score 98%**	**High Accuracy**

Chapter 8

Conclusion and Future Work

In this study, we investigated the use of convolutional neural networks (CNNs) on brain MRI images to detect brain tumours. Early detection of brain tumours is essential to launching prompt therapies and minimising any possible harm these tumours may do to other tissues. We evaluated the performance of different brain tumour detection methods and compared their efficacy.

We discovered through our research that using CNNs to detect brain tumours produced incredibly promising outcomes. The accuracy values of the CNNs were exceptionally high, ranging from 98% to 99.25% on average. This high level of accuracy shows how effective CNNs could be in the early diagnosis of brain tumours.

The suggested methodology included a number of steps, such as pre-processing of the brain picture, segmentation, feature extraction, grouping, and tumour detection. Every level was essential to the algorithm's overall accuracy and efficacy. The dropout idea has also helped me lessen the model's overfitting. It worked well. Brain image enhancement was made possible by using the right pre-processing methods, and tumour locations were precisely segmented using segmentation. Techniques for feature extraction gathered pertinent data, enabling efficient grouping and later tumour diagnosis.

Our choice to concentrate on MRI pictures in this study was furthered by the fact that the use of MRI imaging showed superiority over computed tomography (CT) scans in terms of detail and consistency. MRI scans' increased level of resolution made it possible to identify and characterise tumours more precisely.

Overall, our study adds to the body of knowledge already known about brain tumour identification using CNNs. The success rates show how effective CNN-based methods may be in clinical settings. To assess the robustness and generalizability of the suggested methods across various datasets and populations, additional study is necessary.

The effective use of CNNs for brain tumour detection offers up new opportunities for the creation of automated systems that can help radiologists and other medical professionals make accurate early-stage diagnoses of brain tumours. Through timely interventions and treatment planning, this can ultimately result in better patient outcomes.

Our study's findings demonstrate CNNs' effectiveness in detecting brain tumours and their potential to completely change the way neuroimaging diagnostics is done. Future improvements to CNN designs, training approaches, and data augmentation methods may improve the precision and dependability of these systems. We can open the door for better medical procedures and ultimately help save lives by utilising the potential of artificial intelligence and deep learning.

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